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The forecasting accuracy of models of post-award network deployment: An application of maximum score tests

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ABSTRACT

Each mobile network operator's spectrum is assigned by national governments. Licenses awarded by auctions are tied to post-award network deployment obligations. Using data on 18 countries for the period 2000–2007, this study is the first to empirically forecast aftermarket performance by analysing whether these conditions are met in a timely fashion. The forecasts are conditioned on macroeconomic and market conditions, and package attributes. The models are evaluated based on Mayer and Wu's (in press) maximum score tests. Traditional probit models are not robust to error misspecifications. However, Manski's (1975, 1985) maximum score estimator only imposes median independence, and allows arbitrary heteroskedasticity. One obstacle to empirical implementation is the fact that the asymptotic distribution of the estimator cannot be used for hypothesis testing. Mayer and Wu address the problem using a 'discretisation' procedure. The tests do not impose additional assumptions on the data generating process, require a shorter computational time than subsampling, and allow the models to be misspecified. The test statistics reflect differences in forecasting accuracy under the null and alternative hypotheses.

1. Introduction

Third generation (3G) mobile telephony is a packet-based broadband technology providing enhanced services such as voice, text and high-speed data. There is consensus among most economists that auctions are the preferred mechanism by which to assign the radio spectrum.[1]

National regulatory authorities often seek mobile network operator (MNO) commitments in order to improve social welfare through aftermarket performance obligations contained in licence tender documents. Network coverage and time to deployment obligations are arguably the most important considerations to regulators (Börgers et al., 2002; Hazlett & Muñoz, 2009; Klemperer, 2002; McMillan, 1995). The specific coverage and time requirements imposed by regulators through license agreements vary by country. For all variations, however, unfulfilled obligations entail significant costs, and consequently, whether the commitments are met or not is an important policy issue. Given the award process and market conditions, it is critical for policymakers to be able to forecast whether the realised network coverage will meet both the coverage and time requirements, and in particular, whether the required coverage will be met in a timely fashion. Such forecasts can

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[1] Using the price system to assign spectrum licences via an auction is based on economic efficiency arguments (Cramton, 2002). Other benefits from using auctions include: revenue maximization (Cramton, 2001; Hazlett & Muñoz, 2009; Klemperer, 2002); speed and cost-effectiveness (Börgers, Maasland, & Moldovanu, 2002; Sokol, 2001); and objectivity and transparency (Börgers et al., 2002; Prat & Valletti, 2000).

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be used to improve licence agreements and the award process, for example.

Since the variable of interest is binary,[2] the problem naturally fits into the general framework of forecasting binary responses. Candidate forecasting models include standard probit models that offer asymptotically efficient coefficient estimators under normally distributed errors. Although precise coefficient estimates might help motivate a forecasting model, they do not necessarily guarantee more accurate forecasts. Moreover, the underlying model might be misspecified, which makes the estimation properties uncertain. A well-known limitation of probit maximum likelihood is that the estimator is inconsistent if the distribution of the error term is misspecified (Greene, 2012, p. 693). However, an alternative approach, Manski's (1975, 1985) maximum score estimator (MSCORE), only requires that an assumption of median independence be met for consistency.[3] One obstacle to MSCORE implementation is the fact that the asymptotic distribution of the estimator cannot be used for hypothesis testing. Accordingly, Mayer and Wu (in press) propose a 'discretisation' argument in order to circumvent the MSCORE asymptotic distribution problem, and to enable hypothesis testing. Importantly, the tests do not impose additional assumptions on the data generating process, require less computational time than subsampling, and allow the models to be misspecified. The test statistics reflect differences in forecasting accuracy under the null and alternative hypotheses.

The contributions of this paper are twofold. Namely, the study is the first to provide MSCORE forecasts of whether coverage obligations are met (measured in terms of realised timely aftermarket network deployment) using annual panel data from 18 countries for the period 2000–2007.[4] Second, the MSCORE (in-sample and out-sample) forecast accuracy is compared with that of a probit binary response model. These tests of comparative forecast accuracy (model evaluation) are the first application of the Mayer and Wu (in press) maximum score test.

The empirical findings are intended to provide regulators with information on the means by which they can ensure timely network deployments better. The structure of the remainder of this paper is as follows. Section 2 describes the general forecasting problem and the forecasting rules based on probit and MSCORE estimates. Section 3 describes the hypotheses of interest and the maximum score test. Section 4 describes the data, while Section 5 presents the empirical model and results. Section 6 concludes.

2. Binary response forecasting problem

The general aim is to forecast the binary response y based on observed values of a vector of k observed variables x.[5] In this application, y indicates whether the realised network coverage meets the conditions imposed by the regulators, and x is a vector of variables that reflect the economic, mobile market and license conditions and the award process. The best forecasting rule minimizes the specified expected loss function, which, in turn, depends on the response probability, $P(y = 1|x)$. A standard specification of the latter (Manski, 1985) is a binary response model with median independent errors and regressors:

$$y = I(x\beta + \varepsilon \geq 0) \qquad \text{med}(\varepsilon|x) = 0 \quad \forall x, \tag{1}$$

where $I(\cdot)$ is an indicator function, β is an unknown coefficient vector, and ε is an error term. It follows from Eq. (1) that:

$$P(y = 1|x) \geq 1/2 \Leftrightarrow x\beta \geq 0. \tag{2}$$

Let y^f denote a forecast of y. Assigning equal weights to under- and over-predictions, the absolute loss function analyzed by Manski and Thompson (1989, p. 101) is:

$$L(y - y^f) = I(y = 1, y^f = 0) + I(y = 0, y^f = 1). \tag{3}$$

It follows from Eqs. (1) and (2) above and Proposition 2 of Manski and Thompson (1989) that the best forecasting rule (in the sense of minimising the expected loss $E[L(y - y^f)]$) is:

$$y^f = I(x\beta \geq 0). \tag{4}$$

The implementation of Eq. (4) requires an estimator of β computed from a sample of n observations on y and x. Two potential methods are PML and MSCORE. MSCORE was originally proposed by Manski (1975, 1985), and is defined as the value of β that maximises the sample score function, $S_n(\beta)$, i.e., the fraction of correct in-sample forecasts:

$$S_n(\beta) = \frac{1}{n}\sum_{i=1}^{n} y_i I(x_i\beta > 0) + (1 - y_i)I(x_i\beta \leq 0). \tag{5}$$

MSCORE is consistent under Eq. (1) and random sampling, provided that the distribution of x satisfies mild regularity conditions (Manski, 1985). In contrast, consistency for PML requires the additional assumption that the conditional distribution of ε given x is standard normal.

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2 All tender documents are reviewed. For each licence, the required percentage coverage is recorded, together with the minimum time required to achieve that coverage. Only when both goals are achieved is the variable equal to 1, otherwise it is 0.

3 In the binary choice model, the observed outcome y_i is determined by the latent regression, $y_i^* = x_i'\beta + \varepsilon_i$: $y_i = I(y_i^* > 0)$, where $I(\cdot)$ denotes the indicator function. MSCORE is defined as the value of β that maximises the score function, which is the number of times that $y_i = 1$ is predicted correctly by $x_i'\beta > 0$ and $y_i = 0$ is predicted correctly by $x_i'\beta < 0$:

$$\sum_{i=1}^{n}[y_i I(x_i'\beta > 0) + (1 - y_i)I(x_i'\beta \leq 0)].$$

Substituting $1 - I(x_i'\beta > 0)$ for $I(x_i'\beta \leq 0)$ in the score function, this is equivalent to maximising

$$S_n(\beta) = n^{-1}\sum_{i=1}^{n}(2y_i - 1)I(x_i'\beta > 0).$$

Manski (1985) proves the strong consistency of MSCORE under the assumption $\text{MED}(y_I^*|x) = x_i'\beta$ for a random sample of observations. The linear median assumption is less restrictive than other assumptions which are used for the binary response model. It allows for arbitrary conditional heteroskedasticity for ε, and does not require $\Pr[y_I^* > 0|x_i]$ to be an increasing function of $x_i\beta$ (Manski, 1985). These results can be extended to a linear α-quantile problem $Q_\alpha(y|x) = x\beta_\alpha$ with $\alpha \in (0, 1)$. This is equivalent to assuming that the error term has a zero α-quantile, conditional on the regressors, $Q_\alpha(\varepsilon_i|x) = 0$.

4 The forecasts are conditioned on macroeconomic and market conditions, and package attributes.

5 A detailed analysis of the problem is provided by Manski and Thompson (1989).